EFFICIENT ECG SIGNAL COMPRESSION USING ADAPTIVE HEART MODEL

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Abstract- **This paper presents an adaptive, heart-model-based ECG compression method. After a conventional pre-filtering the waves from the signal are localized and the model's parameters are determined. The structure of the algorithm allows real-time adaptation to the heart's state. The compression, for better comparison, was performed for one and more channels from the MIT/BIH database samples. The compression ratio depends on the maximal allowed root mean square reconstruction error (RMSRE). As a second classification criterion we applied the performance of the signal detection method from the compacted data. We used an adaptive entropy encoder to reduce the redundancy. The major advantage of this method is the possibility to accomplish a real-time, adaptive and patient specific encoding with relatively low computational power, ideal for telemetry measurements.** **This research is supported by the Hungarian Foundation for Scientific Research, Grant T29830 and FKFP0301/0999 Project.**

Keywords - **ECG signal analysis, QRS detection, heart model, on-line processing, telemetry.**

I. INTRODUCTION

The computerized ECG processing [1,2], after several years of improvement, can be considered a well-developed application. Many digital ECG analyzing systems, most of which are based on recognition and clustering algorithms, have to recognize any potentially dangerous arrhythmia with at most a few seconds delay. This task has to be accomplished in case of the telemetry systems too [3].

A distributed Holter telemetry [4] system with low bandwidth channels needs signal compression for efficient functioning. Beside these systems the central databanks (consisting million of ECG recordings) also needs efficient signal compression [5].

Due to the collected noise during measurement there is almost no reason to use loss-free compression [6,7]. We focused on loose methods because the measurement noise and final reconstruction possibility, using medical knowledge. Moreover, that small recovery error seldom disturbs the accurate diagnosis [8].

Almost all biological signals are more complex, than being possible to represent correctly with linear models, so we used exponential parameterization in order to determine the signal's main characteristics. This model type could be used at filtering, determination and compression too.

The compression performance criterion includes two factors: diagnosis performance from reconstructed signal and the amount of the compacted data. According to these facts, the root mean square reconstruction error (RMSRE) and the required terms of bits per second (RTBS) criteria reflect the truth in almost every case [9].

The whole method consists of preprocessing, filtering, evaluation, model parameter estimation, signal reconstruction and error evaluation after post-filtering and compression [10].

Creating a heart model [11] increases the performance of evaluation, because the computer, when applying traditional signal processing algorithms, recognizes lots of waves, but it does not really "understand" what is happening. This problem can be handled only if the computer knows the origin, the formation of the ECG signal [4].

II. MATERIALS AND METHODS

This algorithm was tested using the ECG registrations of MIT-BIH database, sampled at 360 Hz with 11-bit resolution. The bulk of these files contain two channels.

The following ECG compression algorithm is based on the adaptive long and short-term prediction.

It consists of the following steps:

- Pre-filtering;
- Segmentation into R-R intervals;
- Building up template bank for R, T and P waves;
- Determine the model's parameters;
- Performing optimal filter using pattern database and the model-based estimation;
- Adaptive smoothing of the output data;
- Estimation and determination of the residual signal;
- Back-estimation to verify the detection rate;
- Entropy coding;

A. Pre-filtering

This step is absolutely necessary because of the necessity of the accurate R, T and P wave detection for segmentation. Let $\hat{X}_L(n)$ and $\hat{X}_R(n)$ the n-th left and right aimed estimation, defined as:

$$\hat{X}_L(n) = p_L \cdot \tilde{X}_L(n) = p_L \cdot \sum_{i=-q}^{q} a_{L,i} \cdot X(n-i) + (1-p_L) \cdot \sum_{i=1}^{q} b_{L,i} \cdot \hat{X}_L(n-i) \quad (1)$$

$$\hat{X}_R(n) = p_R \cdot \tilde{X}_R(n) = p_R \cdot \sum_{i=-q}^{q} a_{R,i} \cdot X(n-i) + (1-p_R) \cdot \sum_{i=1}^{q} b_{R,i} \hat{X}_R(n+i), \quad (2)$$

where $a_{L,i}$, $a_{R,i}$, $b_{L,i}$ and $b_{R,i}$ are prediction coefficients, p_L and p_R are balance probabilities determined by the dispersions $s_{\hat{X}_L - X}(n,l)$, $s_{\hat{X}_R - X}(n,l)$, $s_{\tilde{X}_L - X}(n,l)$ and $s_{\tilde{X}_R - X}(n,l)$.

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For better separation of the signal from the noise, the length l ought to select more than one R-R period.

In real time processing the estimation is delayed with at least $3 \cdot q$, but preferably with more than one R-R interval, in order to minimize the differences of the efficiency between $\hat{X}_L(n)$ and $\hat{X}_R(n)$; $(p_L \geq p_R; p_L + p_R = 1)$.

The result of this procedure is $\hat{X}(n)$ obtained by:

$$\hat{X}(n) = p \cdot \sum_{i=-q}^{q} a_i \hat{X}_L(n-i) + (1-p) \cdot \sum_{i=-q}^{q} b_i \hat{X}_R(n-i) . \qquad (3)$$

The estimation factors $a_{L,i}$, $a_{R,i}$, $b_{L,i}$, $b_{R,i}$, a_i and b_i are obtained by a genetic algorithm [10]. Although $s_{\tilde{X}_L - X}(n,l)$ and $s_{\tilde{X}_R - X}(n,l)$ may take various values, the calculated probability p rarely is outside of the interval (0,4-0,65).

B. Segmentation into R-R intervals

The data separation is performed by using some pre-determined information, in order to build up the starting pattern collection. Then a neural network [9,12] with a nonlinear hidden layer detects the R waves. The major problem is to resolve the cases when the patient's QRS wave's pattern differs much from "average waveforms". In this case a deeper analysis is necessary, which is processed using hearth model based signal estimation. This is an unavoidable step of the filtering and detection.

C. Construction of the R, T and P waves shape selection and determine the heart model's parameters

The main characteristic shapes of a normal ECG signal are R, T and P waves. While performing real-time analysis, the wave-bank can be slightly modified. The changes are based on auto-correlation of the pre-filtered signal and the template's elements.

The heart model, to verify the anatomic construction of these signals in order to develop the model and to detect possible hearth malfunctions must process these waves. In this step are determined the model's parameters, too.

D. Performing optimal filter using pattern database and the model-based estimation

The optimal filter bases on the pre-filtered signal and the template bank. Let

$$\tilde{X}(n) = p_{F,X-\tilde{X}}(n) \cdot \sum_{i=-q}^{q} a_{F,i} X(n-i) +$$
$$(1 - p_{F,X-\tilde{X}}(n)) \cdot \sum_{i=-q}^{q} b_i B(m,i) \qquad (4)$$

be the processed data. The low value of the p_F (p_F <0.2) justifies the need of the collection B, whose *m*-th element has the maximal correlation value with X(n). The model estimation determines the B collection elements.

E. Adaptive smoothing of the output data

After the signal is filtered, a smoothing operation should be performed to reduce the size of the compacted data. The method's strength should be selected in accordance with the diagnosis performance decrease from the recovered signal. The main aim of this algorithm is to decrease the length of the compressed signal and to keep the data quality as high as possible. Let be

$$\tilde{X}_{[sm.]}(n) = \frac{\sum_{i=1}^{k-1} \tilde{X}_{[sm.]}(n-i \cdot t) + \tilde{X}(n)}{k} \qquad (5)$$

where $k = 2^j; (j \in N)$, $t \in N$ and N is the natural set.

Normally the adjacent samples are highly correlated, and we select the positive integer t that minimizes the auto-correlation function of the ECG signal. Usually the sampling delay t is about half a QRS complex duration. Because the QRS complex contains the bulk of the signal's power, the R wave is nearly symmetrical and in normal case Q and S are negative, it is clear, that the t sampling period delay is optimal. In the meantime this value should be adaptively changed.

The inverse transform is given by:

$$\tilde{X}(n) = k \cdot \tilde{X}_{[sm.]} - \sum_{i=1}^{k-1} \tilde{X}_{[sm.]}(n - i \cdot t) . \qquad (6)$$

In the meantime of the transform, the values of $\tilde{X}(n)$ and $\tilde{X}_{[sm.]}(n)$ can be modified with $\frac{k}{2}$ in order to reduce the reconstruction error or the dispersion of the smoothed signal. The efficiency of this algorithm highly depends on the chosen values for k and t.

F. Estimation and determination of the residual signal

Because the scatter of the filtered and optionally smoothed signal $s_{\tilde{X}_{[sm.]}}(n,l)$ is too high to allow sufficient compression rate, a linear prediction transform is needed. This method eliminates the redundancy due to correlation between adjacent samples and beats.

The resulting data

$$Y(n) = p_{E,\tilde{X}_{[sm.]}-B(m)}(n) \cdot \sum_{i=1}^{q} a_{E,i} \tilde{X}(n-i) +$$
$$\left(1 - p_{E,\tilde{X}_{[sm.]}-B(m)}(n)\right) \cdot \sum_{i=-q}^{q} b_{E,i} B(m,i) \qquad (7)$$

determine the residual $r(n) = Y(n) - \tilde{X}_{[sm.]}(n)$.

G. Back-estimation to verify the detection rate

After determining the residual signal we proceed a verifying process to determine the performance decrease due to compression. More iterations should be calculated to determine the optimal set of parameters. This means that, when the performance decreases significantly, we have to look for a better solution (a better set of parameters).

H. Entropy coding

The estimation errors have nearly normal distribution. In order to reduce the length of the residual data an entropy coding is needed. In order to minimize the loss we use an own adaptive coding method.

For every moment we determine the dispersion $s_r(n,l)$ and the probability $p_{s_r(n,l)}(r(n,l))$ of the errors. If the quantum is $q = 2^u$, where u is the length in bits of the word, the output value is obtained by:

$$N_{[act.]}(n,k) = I_1(n-k+1) + p_1(n-k+1)\cdot I_2(n-k+2) + \ldots$$

$$\ldots + \prod_{i=1}^{k-1} p_i(n-k+i)\cdot I_k(n)\,, \qquad (8)$$

where $p_i(n-k+i) = p\big(r(n-k+i),l\big)$ and

$$I_{k-i}(n-i) = \int_{-\infty}^{r(n-i)} p_{k-i}(n-i)\cdot dr\,.$$

III. RESULTS

To allow a better performance estimation we used the MIT-BIH arrhythmia database for evaluation. The performance is determined by the number of estimation parameters, smoothing strength, resolution and sampling rate.

Due to hearth model estimation and the advanced verifying algorithm, the resulting file size is considerably decreased.

Table I. illustrates the smoothing and power's effect on the file MIT 105.

TABLE I.
THE SIZE OF THE COMPACTED SIGNAL FOR DIFFERENT CASES

Power	Loss-free RMSRE=0	Smoothing I. RMSRE=3%	Smoothing II. RMSRE=9,7%
4	185457	22567	10223
8	177876	20986	9844
16	172546	19443	9223
32	169452	19104	8997

The sampling rate has minor effect when increased above 200Hz, but a better resolution always increase the performance, due to the better estimation and lower reconstruction errors.

TABLE II.
RESOLUTION'S EFFECT (COMPARED 8 AND 11 BIT SAMPLES)

Power	Loss-free, 11 bit Smp.=180Hz	Loss-free, 11bit Smp.=360Hz	Loss-free, 8 bit Smp.=180 Hz
4	179799	175485	212995
8	173456	170872	204457
16	169553	167524	200782
32	167495	164790	197904

The entropy coding can decrease about 10 times the theoretical "waste", compared with Huffman coding, during signal compacting.

TABLE III.
THE ENTROPY CODER'S PERFORMANCE FOR DIFFERENT FILES

File (MIT-BIH)	Theoretic Entropy 32 parameters	Huffman code size 32 parameters	New coding 32 parameters
104	170889	202158	173238
105	167021	197384	169452
108	172093	204214	175027
201	156878	185962	159003
203	185872	218977	188409
222	168126	199880	170981
228	181774	214708	184095

These files were selected from the arrhythmia database due to their higher noise or artifact level. For all the studied registrations, the performance was better than Cuiwei's QRS detection technique [7,13].

IV. DISCUSSION

By increasing the parameter number above 32, the performance will not increase considerably. This performance can be boosted only using wave-shapes generated by the hearth model. To maximize the performance in this way we need further study.

The main goal of Table I. is to clarify, that in case of exact coding higher resources are needless. A subsequent filtering applied at the recovery of a smoothed signal needs a lot of computation time, its speed is comparable with the compaction's one.

The resolution reduction can create significant decrease of the condensed file (Table II.) due to the efficient filter method (equation: 1-4). If the sampling rate is lower, the compressed data is shorter only at loss-free coding. This fact is unambiguous, lower quantity of information means more redundancy. Above 200Hz sampling rate the performance increase due high sampling rate is minimal.

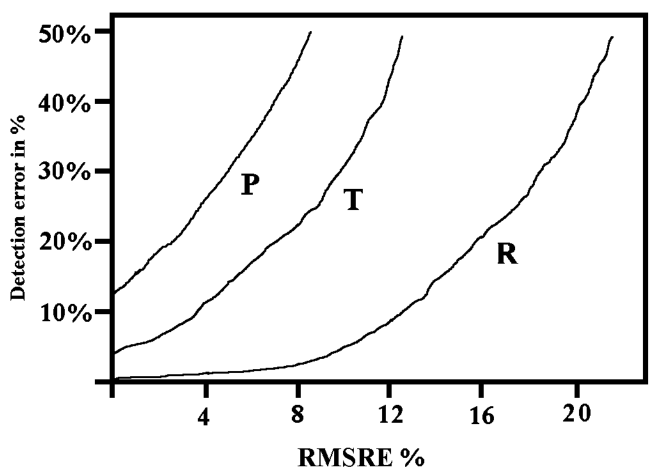

Fig. 1. The recognition ratio of R, T and P waves plotted against RMSRE

Table III. illustrates the compaction effectiveness for the most perturbed files, whose noise level and missed R wave detection rate was maximal [7]. The new coding algorithm (equation: 8) has far better results than the adaptive Huffman coding. Gauss

distribution reflects almost truly the real situation, its change is not recommended without further knowledge.

The smoothing strength should be selected by k and t (formula: 5,6). Experiments show that (Figure 1) R wave can be accurately recognized even if RMSRE is about 10 %. For T and P wave detection [7,9] the root mean square error must not exceed 3-5 % of the signal's power. S (J), Q points and U wave cannot be recognized in most of the cases if RMSRE is higher than 1 %.

V. CONCLUSION

The experimental real-time processing with this method needs a powerful computer. In Holter telemetry [4] and diagnostic systems, where a vast amount of data are acquired and transmitted by radio wave, the compression is an unavoidable step of the computerization.

Sophisticated long computation (due to the hearth model) and lingering unpack of the signal could be the major disadvantages of this process. Although quite often the calculation term doesn't admit on-line computerization (in multitasking mode), the rapid evolution of the computers will shortly change this fact.

REFERENCES

[1] Hajime Murakami, Koichi Shimizu, Katsuyuki Yamamoto, Tomohisa Mikami, Nozomu Hoshimiya, Kimio Kondo, "Telemedicine Using Mobile Satellite Communication", *IEEE Trans. Biomed. Eng*., vol. 41, pp 489-497, May 1994.

[2] C. S. R. Krishnan, D. Antony Louis Piriyakumar, C. Siva Ram Murthy, A Note on "Task Allocation and Scheduling Models for Multiprocessor Digital Signal Processing", *IEEE Trans. Signal Processing*, vol. 43, pp 802-805, March 1995.

[3] S. M. Szilágyi, "Telemetry, Analysis and On-line Processing of the ECG Signal", *microCAD '97 International Computer Science Conference*, Miskolc, February 26-27, 1997.

[4] S. M. Szilágyi, L. Szilágyi, A. Frigy, A. Incze, "Holter Telemetry in the Study of Heart Rate Variability", *Romanian Heart Journal*, Vol. 2., Nr. 6, 1996, p. 143.

[5] S. M. Szilágyi, I. Z. Moldován, L. Szilágyi, "Hardware and Software Problems of the ECG Signal Processing", *Biomedical Engineering Conference*, Budapest, May 8-10, 1996.

[6] W. Philips, "ECG Data Compression with Time-Warped Polynomials", *IEEE Trans. Biomed. Eng*., vol. 40, pp 1095-1101, November 1993.

[7] Cuiwei Li, Chongxun Zheng, Changfeng Tai, "Detection of ECG Characteristic Points Using Wavelet Transforms", *IEEE Trans. Biomed. Eng*., vol. 42, pp 21-27, January 1995.

[8] G. Nave, A. Cohen, "ECG Compression Using Long-Term Prediction", *IEEE Trans. Biomed. Eng*., vol. 40, pp 877-885, September 1993.

[9] Qiuzhen Xue, Yu Hen Hu, W. J. Tompkins, "Neutral-Network-Based Adaptive Matched Filtering for QRS Detection", *IEEE Trans. Biomed. Eng*., vol. 39, pp 317-329, April 1992.

[10] L. Szilágyi, S. M. Szilágyi, "ECG Signal Compression using Genetic Algorithm", *2nd Scientific Conference of Young Engineers*, Cluj, March 21-22, 1997.

[11] S. M. Szilágyi, "The Limits of Heart-Model-Based Computerized ECG Diagnosis", *Proceedings of World Congress on Medical Physics and Biomedical Engineering*, July 23-28, 2000, Chicago, IL. USA, WE-CXH-147.

[12] S. M. Szilágyi, "Non-Linear Adaptive Prediction Based ECG Signal Filtering", *Proceedings of the 21st IEEE Conference on Engineering in Medicine and Biology*, Atlanta, pp 286, October 12-16, 1999.

[13] S. M. Szilágyi, L. Szilágyi, "Wavelet Transform and Neural-Network-Based Adaptive Filtering for QRS Detection", *Proceedings of World Congress on Medical Physics and Biomedical Engineering*, July 23-28, 2000, Chicago, IL. USA, TU-FXH-92.